



Modelling diffusion feedbacks between technology performance, cost and consumer behaviour for future energy-transport systems



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HIGHLIGHTS

- Petrol hybrids achieve mass diffusion by 2025 from competitive cost and performance.
- BEVs are only competitive by 2050 when consumers account for lifecycle costs.
- Investment must reach 35% p.a. growth in alternative fuel market for mass diffusion.
- Rate of diffusion is a function of technological and behavioural factors interacting.

ARTICLE INFO

Article history:

Received 12 July 2013

Received in revised form

18 October 2013

Accepted 9 November 2013

Available online 25 November 2013

Keywords:

Technology performance

Innovation diffusion

Consumer behaviour

Electric vehicles

Sustainable energy

ABSTRACT

Emerging technologies will have important impacts on sustainability objectives. Yet little is known about the explicit feedbacks between consumer behaviour and technological change, and the potential impact on mass market penetration. We use the UK as a case-study to explore the dynamic interactions between technology supply, performance, cost, and heterogeneous consumer behaviour and the resulting influence on long term market diffusion. Simulations of competing vehicle technologies indicate that petrol hybrids (HEVs) dominate the market over the long-term because they benefit from improved performance and are able to reach the steep part of the diffusion curve by 2025 while competing technologies remain in the early stages of growth and are easier to displace in the market. This is due to the cumulative build-up of stock and slow fleet turnover creating inertia in the technological system. Consequently, it will be difficult to displace incumbent technologies because of system inertia, cumulative growth in stock, long operational life, and consumer risk aversion to new unproven technologies. However, when accounting for both technological and behavioural change, simulations indicate that if investment can reach 30–40% per annum growth in supply, combined with steady technology improvements, and more sophisticated agent decision making such as accounting for full technology lifecycle cost and performance, full battery electric vehicles could displace the incumbent system by 2050.

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1. Introduction

Global sustainable energy and environment policies have increased the need to understand how new energy-saving technologies diffuse into the market [1]. The transport sector is a major source of unsustainable energy use currently contributing

~20–25% global CO₂ emissions [2]. Energy use and CO₂ emissions in transport are closely linked to vehicle engine efficiency i.e. fuel requirement per unit distance travelled and the relative carbon content of fuel e.g. gasoline, biofuel, electricity. Improved fuel economy through advancements in vehicle technology has come to be viewed by governments and industry as a key strategy to reduce transport energy intensity [3]. Although the potential benefits of advanced vehicle technologies (AVTs) have been demonstrated [4–6] many uncertainties exist over the scale and timing of their market diffusion. Importantly, it is not well understood how policy can influence technological diffusion [7] characterized by the phasing in and out of technologies [8].

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Future trends in passenger car markets are often modelled as part of large economy-wide models which can be characterized as 1) supply-driven forecasts that assume aggressive industry investment and targeted policy interventions or 2) demand-driven forecasts that assume rapid consumer adoption based on changes in economic parameters such as reduced price differentials between competing technologies [9]. The former approach assumes that massive investments in technology supply will be met by sufficient demand, while the latter assumes that rapid consumer adoption will be met by sufficient supply. We build on those modelling developments but integrate supply and demand side factors and focus on assessing the underlying dynamics between how technology and consumer behaviour interact and change over time and the resulting impacts on mass diffusion. We also develop future scenarios to explore the level of technological and behavioural change necessary to shift towards a more sustainable future energy-transport system.

Mathematical modelling and forecasting the diffusion of technological innovations have been well established since the seminal works of Rogers [10] and Bass [11]. Technology and innovation diffusion theory seeks to explain the factors that determine the rate at which ideas and technologies spread through society [12]. Diffusion theory has typically been applied to consumer durable goods but has found less application to new technologies with environmental benefits. Usha Rao and Kishore [7] argue for the need to build up experience in applying diffusion models to renewable energy technologies (RETs). They indicate that while learning curves have been widely used for economic considerations it is important to consider how policy, social, and technological factors can influence the diffusion process. Although diffusion theory has been applied to conventional vehicles, new vehicle technologies particularly low emission vehicles face similar challenges as RETs such as high capital investment and lack of a level playing field while having similar environmental and energy reduction benefits. However, the key difference between RETs and vehicle technologies is that diffusion of the latter will depend upon consumer behaviour [13]. Pacala and Socolow's [14] stabilization wedges target energy-demand behaviour as one of the most cost effective options for decreasing CO₂ emissions. This points to the important, but less understood interplay between how consumer behaviour, particularly purchasing decisions affects the market diffusion of energy-demand technologies, or how changes in those technologies can in turn influence consumer adoption. Other studies have applied diffusion curves to AVTs focussing more on system wide and macroeconomic effects [15,16]. Here, we develop a model that examines the underlying dynamic interactions between technology supply and performance, and consumer behavioural preferences. We develop different exploratory scenarios to parameterize the simulation model in an effort to explore possible technological diffusion trajectories to meet energy and climate policy. The paper proceeds with methods and data, simulation results, conclusions and limitations of the work.

2. Methods and data

2.1. Model derivation

The following summarizes the full methods developed in Ref. [43]. *Supply-side dynamics* – We develop a bounded geometric growth model that simulates an evolving vehicle technology stock in single year time steps over the period 2000–2050. Simulations are used to analyse the rate of technology adoption, substitution and decay of competing technologies within a single market. The

model is derived as follows: Growth of the total vehicle market, TVM_n in year *n* is given by,

$$\text{TVM}_n = [\text{TVM}_{n-1} * \Phi_{\text{TVM}}] + [\text{TVM}_{n-1} - (\lambda * \text{VAD})] \quad (1)$$

where Φ_{TVM} is a growth function exogenously inputted into the model representing total market demand for passenger cars in each time step *n*. λ is a decay function where a fraction of TVM_{n-1} is subtracted at each time step *n*, based on vehicle age distribution, VAD which follows a sigmoid curve derived from 20 years of UK historical vehicle licensing statistics [17]. The total vehicle market, TVM is disaggregated into the total vehicle stock TVS_{jn} of technology *j* in year *n* given by,

$$\text{TVS}_{jn} = [\text{TVS}_{jn-1} * \Phi_{jn}] + [\text{TVS}_{jn-1} - (\lambda * \text{VAD})] * [P_{ijn}] \quad (2)$$

where Φ_{jn} is the growth rate of technology *j* in year *n*. This is exogenously inputted into the model, which can be adjusted to simulate industry investment or targeted government policy for specific vehicle technologies representing the 'supply-push' dynamic of the model. We normalize *N* the growth of individual technologies TVS_{jn} to the total vehicle market TVM_n by the following algorithm,

$$N = \text{TVM}_n / \sum_{j=1}^J \text{TVS}_{jn} \quad (3)$$

$$\text{TVS}_{jn} = \text{TVS}_{jn} * N \quad (4)$$

Resulting in,

$$\text{TVM}_n = \sum \text{TVS}_{jn} \quad (5)$$

TVM_n therefore serves as an upper bound on geometric growth of each individual technology displaying characteristic logistic curves. This simulates market saturation effects from accumulation of individual technologies over time because TVM_n acts as an upper bound on the growth of individual technologies, TVS_{jn}.

Demand-side dynamics – Agent-behaviour in the form of consumer 'demand-pull' dynamics enters the model as a probability function P_{ijn} which is the probability that consumer *i* will select technology *j* in year *n* based on random utility theory [18–20] where the utility U_{ij} of person *i* from alternative *j* is

$$U_{ij} = \beta_i X_{ij} + \varepsilon_{ji} \quad (6)$$

X_{ij} is a vector of observed variables, β_i is a vector of preferences or tastes for observed variables, ε_{ji} is a random error term representing the unobserved portion of utility, which is assumed to be independently and identically distributed (iid) across alternatives specifically a type I extreme value error term. If the vector of β_i 's are observed P_{ijn} collapses to the standard multinomial logit since ε_{ji} is integrated out, giving

$$P_{ijn} = e^{\sum \beta_i X_{ij}} / \sum_{j=1}^J e^{\beta_i X_{ji}} \quad (7)$$

However, we do not observe β_i and therefore assume preferences can be captured by a probability density $f(\beta|\theta)$ where we specify the functional form $f(\cdot)$ and estimate parameters, θ such as

the mean, μ and standard deviation σ . P_{ijn} therefore takes the form of an open integral,

$$P_{ijn} = \int L_{ij}(\beta) f(\beta|\theta) d\beta \quad (8)$$

which can be numerically integrated by Monte Carlo simulations using the following algorithm [21]: Take a random draw R , of β_n 's from a density $f(\beta_n|\theta)$ such that,

$$(\beta_n) \sim f(\beta_n|\theta) \quad (9)$$

Calculate the conditional probability, L_{ijn} as,

$$L_{ijn} = e^{\sum \beta_i X_{ji}} / \sum_{j=1}^J e^{\beta_i X_{ji}} \quad (10)$$

Repeat R times such that,

$$P_{ijn} = \frac{1}{R} \sum_{r=1}^R L_{ij}(\beta^r) \quad (11)$$

As R increases variance, σ decreases. We calculate P_{ijn} for each time step n and pass the vector back through TVS_{jn} and continue iteration. P_{ijn} is multiplied by TVS_{jn} and therefore conditions the cumulative growth of TVS_{jn} over the modelled period to 2050. We therefore combine Monte Carlo simulations with scenarios widely used in energy systems modelling [3,22]. Internally consistent scenario assumptions allow specification of preferential behaviour for different technology attributes thereby simulating agent heterogeneity. And while these are only exploratory simulations the advantage of this approach is that it allows us to quantify the relative changes in technological performance and consumer preferences to assess long term diffusion.

2.2. Model data

Vehicle stock data are from UK government [17,23] and industry statistics [24]. Vehicle technologies are selected based on the incumbent system and recent UK policy and industry trends towards alternative fuelled vehicles (AFV). The model includes: petrol internal combustion engine (ICE), diesel-ICE, hybrid electric-petrol (HEV), plug-in hybrid electric-petrol (PHEV), pure battery electric (BEV), and hydrogen fuel cells (FC). Technologies and vehicle attributes, X are summarized in Table 1. Attributes are normalized and indexed against petrol before inputted into the model.

2.3. Reference scenario and calibration

In the reference scenario, the model is calibrated to the UK medium size passenger vehicle market and assumes it is representative of the total passenger vehicle stock. The growth of the total vehicle stock (Φ_{TVM}) is set at 1.2% per annum over the projection period (2050). This assumption is based on UK government trend data and macroeconomic forecasts where demand for passenger car travel measured in passenger-km or vehicle-km increased 20% from 1990 to 2006, and is currently on a growth trajectory of 1% per annum [29]. Demand is influenced primarily by GDP and population, which are forecasted to grow per annum 2.5% and 0.5% respectively towards 2050 [22]. To calibrate the model, each technology per annum growth, Φ_{jn} was set at: petrol (1.4%), diesel (11%), HEV (16%), PHEV (10%), BEV (10%) and FC (5%). Based on empirical data [17] to initialize the stock model at the year 2000 it is assumed that the remaining 0.1% of the non-incumbent passenger vehicle stock is comprised of HEV (0.07%), PHEV (0.01%), BEV (0.01%) and FC (0.01%). The decay function, λ which simulates scrappage, is calculated from vehicle age distribution (VAD) statistics [17], where the total passenger vehicle stock is split into seven age segments: 0–1, 1–2, 2–3, 3–4, 4–6, 6–13, and >13 years of age where a low fraction (~5%) of new vehicles (<3 yrs) compared to a high fraction (~70%) of older vehicles (>13 yrs) are scrapped. We currently use the average scrappage rate of 13% per annum, where each technology is scrapped in proportion to the total vehicle stock at each time step, n .

To simulate heterogeneous agent behaviour several density functions can be used for $f(\cdot)$. However, the normal and lognormal distributions are the most common [21]. A lognormal distribution is used if from a theoretical perspective, a beta (β) coefficient has to take the same sign (+/–) for every individual. This is useful for our analysis because it allows us to assume global preferential behaviour for specific vehicle attributes under different scenario assumptions. For instance, purchase price and lack of refuelling infrastructure are major deterrents for adoption of AFVs [3,5]. The reference case therefore assumes people are negatively affected by purchase price and positively affected by vehicle reliability which we proxy as refuelling availability. We therefore specify $f(\cdot)$ as lognormal for purchase price and refuelling availability, making consumer adoption sensitive to high purchase price and poor reliability. Normal distributions are used for all other attributes in the reference case. In subsequent scenarios we vary these distributions to give preferential weighting for other attributes and assess diffusion. For normal distributions, theta (θ) has a mean value ~zero; for lognormal distributions theta is ~1.4, and both distributions have a standard deviation of one. The model is calibrated to 1999–2009 UK historical data [17]

Table 1
Vehicle attribute data for UK.

| Technology | Purchase price (£) | Fuel price (£/100 km) | Fuel efficiency (L/100 km) | Acceleration (0–100 km/h ⁻¹ in seconds) | Range (km on 1 tank/charge) | Environment (WTW GHG gCO ₂ -eq km ⁻¹) | Refuelling availability (%) |
|------------|--------------------|-----------------------|----------------------------|--|-----------------------------|--|-----------------------------|
| Petrol | 10437 | 10.0 | 8.1 | 6.5 | 567 | 163 | 100 |
| Diesel | 12659 | 8.76 | 6.9 | 8.7 | 714 | 155 | 100 |
| HEV | 16407 | 5.88 | 4.7 | 10 | 862 | 140 | 100 |
| PHEV | 25275 | 3.29 | 4.5 | 12 | 764 | 109 | 50 |
| BEV | 20569 | 3.21 | 2.4 | 11 | 117 | 77 | 1 |
| FC | 62750 | 1.37 | 3.9 | 12 | 384 | 73 | 1 |

Data sources [25–27]; U.S. Department of Energy (DOE) Alternative Fuels and Advanced Vehicles Data Centre [28]. Notes: We use refuelling availability as a proxy for reliability which is an important factor in vehicle purchasing decisions [13,16]. Refuelling availability is a relative measure of reliability in consumer decision-making. It does not imply specific numbers of AFV refuelling stations relative to ICEs since this would require normalization against vehicle range. It is assumed that from a consumer perspective there is no range anxiety associated with ICEs and set refuelling availability at 100%. For PHEVs there are currently mixed messages surrounding charging availability in the UK. A Department for Transport [11] study suggests that home charging would not pose a problem for most UK homes. We make a conservative assumption in the reference case for PHEVs assuming 50% of consumers can charge from home. We also assume in the reference case BEV and FC refuelling availability (RA) is far less than ICEs and is arbitrarily set at 1% relative to ICEs.

showing a good fit with an R^2 of 0.9702 with 95% confidence bounds on coefficients.

2.4. High growth scenarios

We now want to explore the impact of high technology growth. Industrialized countries around the world see AFV use, manufacture and development as an important business opportunity. The UK government for example, seeks to position itself as a world leader and has developed high growth scenarios for BEVs and PHEVs from 2010 to 2030. In the government's business-as-usual scenario average per annum growth of BEVs is 29% from 3000 to 500,000 and PHEVs, 48% from 1000 to 2.5 million. Over the same period, the high growth scenario explored by the UK government implies average per annum growth of BEVs at 40% from 4000 to 3.3 million and PHEVs at 57% from 1000 to 7.9 million [30]. This level of market deployment is highly ambitious and dependent upon increasing total production and the number of models offered on market. By 2020, the IEA [31] forecast that up to 40 models of PHEVs and 20 models of BEVs would need to be developed to achieve large-scale adoption. This coincides with total new or replacement models expected to be offered by manufacturers worldwide over the same period. Reflecting the above studies we assume aggressive government support and manufacturer investment setting average per annum growth rates projected to 2050 for petrol (1.4%), diesel (11%), HEV (30%), PHEV (40%), BEV (40%), and FC (30%). Petrol's are set to grow at the same rate as the total vehicle market. Diesel growth rates are extrapolated from 2000 to 2008 UK data [17]. HEV per annum growth rates were $\sim 50\%$ between 2000 and 2008 which are lowered to 30% in our scenarios to simulate a stronger government and manufacturer focus upon PHEVs, BEVs and FCs. This is largely because rapid deployment of these AFVs is expected to be the only way to dramatically decrease passenger transport carbon emissions of $\sim 70\text{--}90\%$ by 2050 [3,30]. We also want to explore the impact of changing supply and demand dynamics on long-term diffusion and therefore extend the simulation time horizon outwards to 2050.

These supply-driven forecasts assume aggressive manufacturer investment and government policy support for AFVs. However, there is a key gap in understanding whether consumer demand will be sufficient to support these rapid levels of deployment. It is also not understood how consumer behaviour will change over time from improved technological performance within a single competitive market. We therefore develop two variants on the high growth scenario showing the impact on diffusion from: 1) changing technological performance and cost, and 2) changes in technology, cost and consumer behaviour.

2.4.1. Technology dynamics

In the UK, between 1999 and 2008 fuel efficiency for medium size petrol cars improved from 39 to 45 miles per gallon (mpg) [32] and between 1997 and 2007 new passenger vehicle emissions improved from 190 to 167 gCO₂/km implying efficiency improvements of $\sim 1.5\%$ per year [33]. The UK government suggests 30% vehicle efficiency savings over the next 5–10 years [33]. Those estimates imply a range of 1.7–2.7% efficiency improvements per year over the period 2015–2020. For this variant the mean approximation of 2.0% per year efficiency gains for petrol's and diesels are used. From 1990 to 2005, the average annual rate of energy density improvements for Li-ion was 7% reaching 450 Wh/L in 2005. Nickel–metal hydride (Ni–MH) reached 350 Wh/L and nickel–cadmium (Ni–Cd) reached 130 Wh/L representing 4% and 1% improvements respectively over the same period [34]. The UK Department for Transport (DfT) [30] assume from 2010 to 2030, BEV efficiency will increase from a current

0.16 kWh km⁻¹ to 0.11 kWh km⁻¹ implying $\sim 2.0\%$ per year gains. We conservatively set efficiency improvements for battery based AFVs at 2.0% per annum similar to ICEs. Corresponding changes to carbon emissions and running costs are made based on a linear relationship between vehicle efficiency and emissions [33,35].

2.4.2. Cost dynamics

Trends in ICE efficiency gains have slowed in recent years with less room to improve than in the past [35]. This means that ICE improvements will come at a higher incremental cost than for battery technologies over time. The UK government suggests additional production costs of $\sim \text{£}1000\text{--}1500$ per vehicle assuming economies of scale are reached, and using the higher value of $\text{£}1500$ implies a 1.4% increase per year in vehicle production costs [33]. We assume that additional production costs are passed on to the consumer increasing the purchase price 1.5% per year. We also assume that AFVs efficiencies will continue to increase but the costs are not passed onto the consumer either through policy or other interventions such as the $\text{£}5000$ capital incentive recently implemented in the UK [36]. That seems optimistic, but using the higher $\text{£}1500$ value for increased ICE production costs related to efficiency improvements, and not passing the additional costs of AFVs to consumers, those assumptions only imply a 1.5% per annum decrease in the price gap between ICEs and AFVs over the projection period. This is conservative compared to other estimates suggesting AFV capital cost reductions of 7% and 6% per year for BEV and FCs respectively [37], or a 70% decrease in battery storage costs over the next 10 years [3].

2.4.3. Consumer dynamics

We now want to show a high growth scenario that simulates heavy industry and government investment (supply-side push) coupled with changing technological performance and fundamental changes in consumer behaviour. Recent survey work in the UK suggests that consumers are particularly sensitive to fuel economy and CO₂ emissions as a proxy for increased environmental concern when purchasing a vehicle [38]. A recent UK study also reported that financial gains from improved fuel economy and government policy, along with environmental appeal were key factors for early adoption of HEVs [39]. Similar results have also been found in empirical work across Europe and the US [40]. To simulate an early adopter profile consumer sensitivity to fuel prices, fuel consumption and carbon emissions are increased. The sensitivity to purchase price and refuelling availability are also maintained to see the relative change in diffusion when accounting for both technological and behavioural dynamics. Scenario assumptions and adjusted input parameters for reference and high growth scenarios are summarized in Table 2.

Table 2
Scenario assumptions and adjusted input parameters.

| Simulations | Petrol | Diesel | HEV | PHEV | BEV | FC |
|---|--------|--------|-----|------|-----|-----|
| 1. Reference scenario | | | | | | |
| Growth p.a. (Φ_{jn}) | 1.4% | 11% | 16% | 10% | 10% | 5% |
| Behaviour assumption: consumers most sensitive to PP, RA | | | | | | |
| 2. High growth scenarios | | | | | | |
| Growth p.a. (Φ_{jn}) | 1.4% | 11% | 30% | 40% | 40% | 30% |
| 2.1 Variant 1 | | | | | | |
| Technology change p.a. | -2% | -2% | -2% | -2% | -2% | -2% |
| (FC, FP, CE) | | | | | | |
| Cost change p.a. | 1.5% | 1.5% | 0 | 0 | 0 | 0 |
| 2.2 Variant 2 | | | | | | |
| Behaviour change | | | | | | |
| Same as variant 1 except consumers most sensitive to PP, FP, FC, CE, RA | | | | | | |

Notes: PP = Purchase price; FP = Fuel price; FC = Fuel Consumption; CE = Carbon emissions; RA = Reliability.

3. Results

3.1. Reference scenario

Fig. 1 shows average probabilities of consumer adoption for each technology over the period to 2035: petrol (35%), diesel (30%), HEV (26%), PHEV (4%), BEV (3%), FC (1%). Between 1999 and 2008, UK average per annum percentage increases in new vehicle registrations were: petrol ~1%, diesel ~10%, HEV ~50%, and all other advanced technologies <8% [17]. The noticeable change in recent years was increasing consumer adoption of HEVs reflected in our model results showing a relatively high probability of adoption. However as a fraction of the total vehicle stock HEVs are marginal shown in the reference diffusion scenario in Fig. 2.

The reference case assumes that consumer preferences, while capturing random behaviour shown by fluctuations over time, do not significantly change over the modelled period. Projections from 2010 to 2035 were also validated against other reference scenarios developed for the UK giving similar results [41,42]. In 2010, the total UK passenger vehicle stock is ~28 million comprised of petrol (78%), diesel (22%), and alternative fuelled vehicles (AFVs) i.e. HEVs, PHEVs, BEVs and FCs (<1%). Based on current consumer preferences the system tips by 2025, when diesel displaces petrol as the dominant technology on market. This trend is also reflected in the European passenger car market with the rapid uptake of diesels in recent years. By 2035, AFVs make negligible market gains. The reference case shows that without immediate and sustained policy intervention combined with aggressive industry investment, AFVs will not be able to compete with incumbent diesel and petrol technologies thereby falling short of stated UK policy goals to decarbonize the transport sector and alleviate oil dependency on foreign reserves [22].

3.2. High growth scenarios

Fig. 3 shows simulation results based on high per annum growth rates implied by UK policy and industry forecasts, but that now account for current consumer preferences. What is interesting to note is that when accounting for current consumer behaviour, even massive supply-side investments representing 40% per annum growth will not result in BEVs and PHEVs overtaking petrol based hybrids over the long term (2050). Fuel cells also remain uncompetitive despite 30% per annum growth. When we account for both

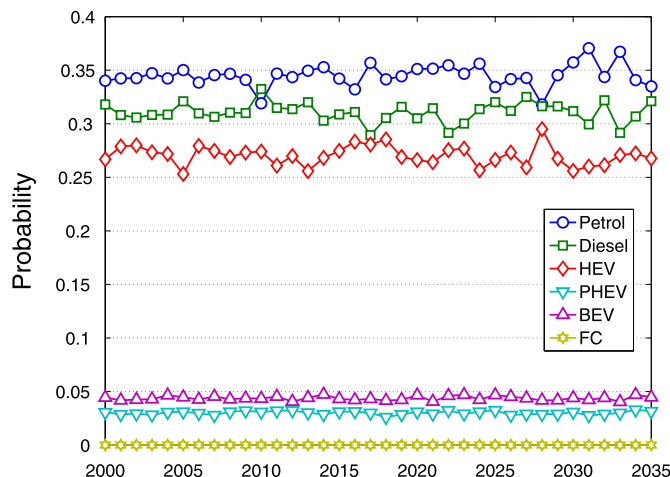


Fig. 1. Probability of consumer adoption for each technology in the reference scenario [43].

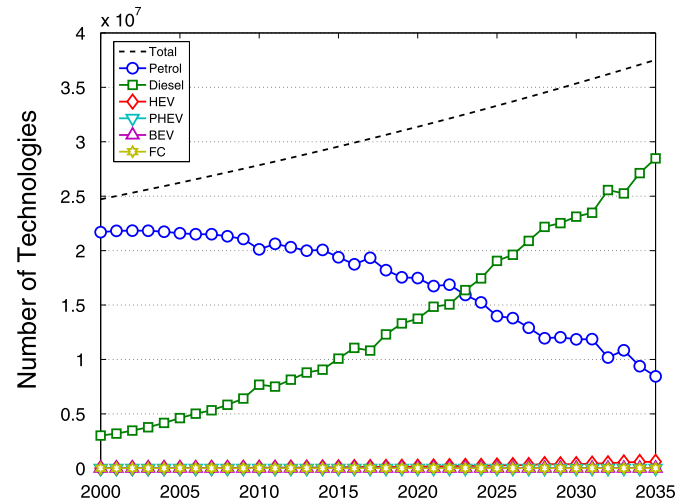


Fig. 2. Technology diffusion reference scenario assuming no change over time in technology performance or agent behaviour over the period to 2035. Calibrated to UK passenger vehicle stock 1999–2009 [43].

supply and demand side dynamics, without fundamental changes in technology and behaviour there is not likely to be a shift towards a low carbon electric transport system as anticipated by government and industry.

Although the previous simulations go beyond extrapolating historical growth trends by explicitly accounting for current consumer preferences, it still assumes that technological performance and consumer behaviour remain static over time. However, based on historical trends we can expect technologies to evolve and improve over time shown by technology learning rates, particularly fuel economy for vehicle technologies [3]. Fig. 4 shows simulation results of diffusion when accounting for changes in purchase price, fuel economy, fuel cost and carbon emissions over the period 2050.

Results indicate that when accounting for improved technological performance combined with current consumer preferences, petrol based hybrids dominate the market over the long-term, even when we assume that incremental costs for battery technologies are not passed onto the consumer. This is because HEVs also benefit from improved performance and are more reliable than BEVs and PHEVs. Importantly, HEVs are able to reach the steep part of the

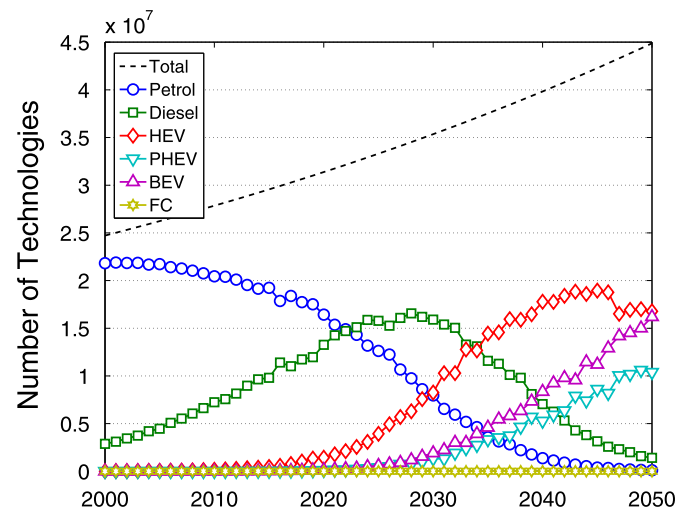


Fig. 3. Long-term high growth diffusion and current consumer preferences.

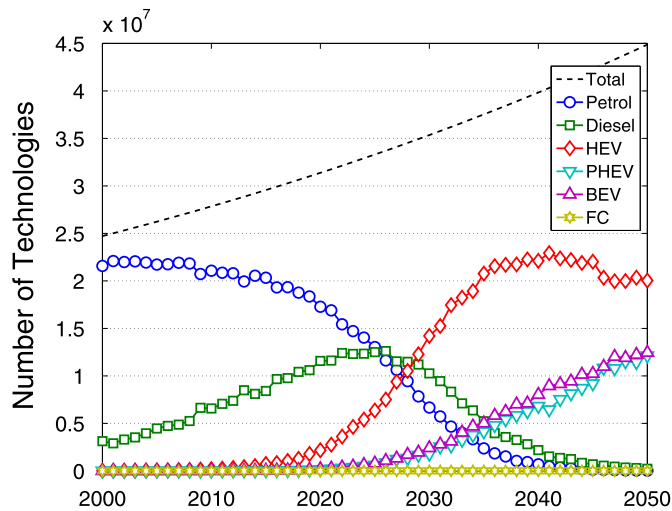


Fig. 4. Variant 1: long-term high growth diffusion scenario accounting for technological change.

diffusion curve by 2025 while BEVs and PHEVs are still in the early stages of growth and are therefore easier to displace in the market. This is due to the cumulative build-up of stock and slow fleet turnover creating inertia in the system. Consequently, it will be difficult to displace incumbent technologies because of system inertia due to large existing stock, cumulative growth in stock, long operational life, and consumer risk aversion to new unproven technologies.

This adds an interesting dynamic to long-term diffusion since much of the focus is on battery technology improvements, without accounting for increasing market competition from higher performing ICE technologies. Nevertheless, Li-ion batteries are in the early stages of development with considerable room to improve when compared to technical advancements made in combustion engine processes. However, ICE technologies can continue to make efficiency gains from non-engine components such as aerodynamics, light-weight materials and low rolling resistance tires [35].

Fig. 5 gives simulation results when accounting for changing technological and behavioural dynamics. We now assume that there are fundamental changes in agent behaviour combined with improving technological performance. This scenario assumes that

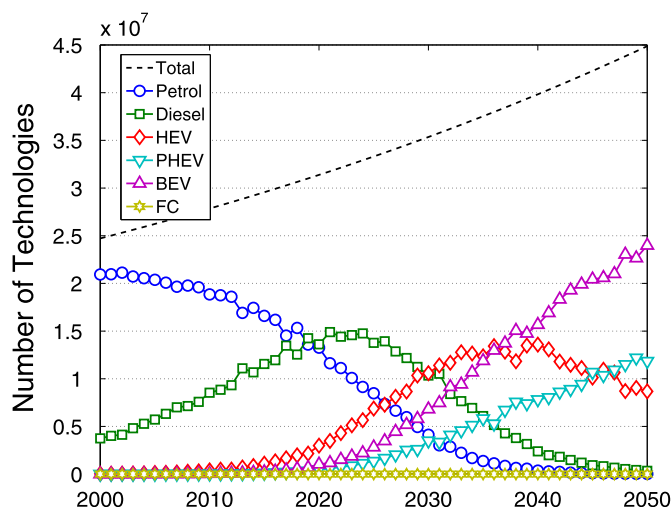


Fig. 5. Variant 2: long-term high growth diffusion scenario accounting for technological and behavioural change.

consumers become more sophisticated in their purchasing decisions and now account for fuel economy, fuel price, and environmental performance. Our results suggest that it will take a combination of massive supply-side investment, combined with improved technological performance, lower relative costs, and fundamental changes in agent behaviour to displace the incumbent system.

4. Conclusions

Although consumer survey's in the UK often show fuel efficiency and increasing environmental awareness [38–40], as important factors in vehicle purchasing decisions the analysis shows that AFVs will not out compete ICEs based on fuel economy or environmental appeal alone. Importantly, recent market gains made by HEVs and potential market share by PHEVs and BEVs in the medium term could be displaced by improvements in ICE's in which risk adverse consumers are already familiar with and have confidence in. Government and industry will need to make other AFV attributes more competitive by lowering upfront costs, increasing vehicle performance, and improving vehicle design and support infrastructure to maximize range and reliability.

The overarching story is that massive investment representing 30–40% per annum growth has to begin immediately in order for AFVs to make any sizeable market penetration over the next 40 years. This is because of the relatively small base from which they grow, combined with a slow fleet turnover of ~10–15 years for ICEs. This indicates the substantial amount of inertia in the incumbent technology system that must be overcome by new technologies in order to achieve rapid diffusion. Over the long-term, if aggressive government and industry investment can reach 40% per annum growth in supply, combined with steady improvements in performance, lower upfront costs, and more sophisticated agent preferences that account for lifecycle cost and performance of the technology, AFVs could displace ICEs by 2050.

We developed future scenarios and simulations to assess how technological and behavioural factors can interact to impact long-term diffusion. It is important to note that our scenarios are not forecasts but internally consistent scenarios in which to explore potential technological trajectories under a variety of circumstances. Our results are therefore limited by our assumptions. We tried to address this to some degree by calibrating the model to the UK vehicle stock and developed three variants of the high growth scenario to test our assumptions. Future work will focus more on the supply side dynamics in particular disaggregating the growth function to account more explicitly for RD&D, spill over effects and resource constraints that will all affect technology design and delivery. We also acknowledge that our specific results are solely based on the UK context and would not hold true for other countries. An important next step would be to apply the methodological framework to other case studies and develop comparative analysis in terms of the specific levels of supply side investment and different levels of consumer behaviour change necessary to achieve mass market diffusion. Despite these limitations we are able to explore how technological performance, cost and consumer behaviour can change over time, interact, and impact upon future energy-transport systems to meet sustainability policy. Our results can help decision makers consider potential trajectories that might otherwise not be expected under more stringent forecasting approaches.

Acknowledgements

We acknowledge generous support from the Oxford Martin School, University of Oxford for funding the fellowship held by one of the authors (MT).

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